Computers and Education: Artificial Intelligence 2 (2021) 100007

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.elsevier.com/locate/caeai

# Modelling and exploiting taxonomic knowledge for developing mobile learning systems to enhance children's structural and functional categorization

MuhammadAzeem Abbas [a,*], Gwo-Jen Hwang [b], Saheed Ajayi [a], Ghulam Mustafa [c], Muhammad Bilal [d]

[a] School of Built Environment, Engineering and Computing, Leeds Beckett University, Leeds, United Kingdom
[b] Graduate Institute of Digital Learning and Education, National Taiwan University of Science and Technology, Taipei, Taiwan
[c] University Institute of Information Technology, Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi, Pakistan
[d] Big Data Enterprise and Artificial Intelligence Laboratory (Big-DEAL), Bristol Business School, University of West of the England, Bristol, United Kingdom

ARTICLE INFO

*Keywords:*
Taxonomic knowledge
Ontology
Mobile learning
Pre-school education
Structural and functional categorization

ABSTRACT

The recent decade has seen increased attention focused on understanding category formation–a cognition ability of preschool aged children. Children organize their knowledge about real-world objects by categorizing them under some common properties or functions. The advancement and popularity of mobile devices with touch screens provide a good opportunity for young children to learn and practice. In this study, an approach that models structural and functional categorization knowledge for developing mobile learning systems with dynamic categorization exemplars is proposed. A mobile application was implemented based on the proposed model for pre-schoolers (aged 3–6 years). Moreover, the quasi-experimental pre-test and post-test method was used to evaluate the effectiveness of the proposed knowledge-based application in terms of categorization ability learning. The results show that the children who experienced dynamically created categorization exemplars from the modelled knowledge achieved increased scores compared to those who followed the traditional teaching using books and worksheets.

## 1. Introduction

Categorizing real-world objects is a fundamental aspect of children's cognition that helps them to make sense of the world around them (Gelman and Meyer, 2011; Giganti and Viggiano, 2015). Moreover, vocabulary acquisition is strongly related with the categorization skill as reported by several researchers (Axelsson and Horst, 2014; Benitez and Smith, 2012; Smith et al., 2010; Zou et al., 2020). Categorization ability works through finding commonalities among category members at their specialized and generalized levels. Surface-level categorization (general) mainly requires apparent perceptual cues, such as colour and shape (Kimura et al., 2018; Namy and Clepper, 2010). However, deeper rational categorization occurs when the function information of a member object is presented to children (Futó et al., 2010; Hernik and Csibra, 2009; Prager et al., 2016).

Following child psychology, educationists have also included the categorization skill as part of the cognitive syllabus in preschool curricula (Moem, 2001; MOES, 2012; Welsh et al., 2010). Formally, the preschool (i.e., ages 3–6) cognitive syllabus includes categorization, relatedness, spatial concepts, mathematics, science processes, and reasoning & problem solving. It has been reported that object categorization can be enhanced by exposing children to multiple exemplars with perceptually variable structural and functional commonalities (Axelsson and Horst, 2014; Quinn et al., 2020).

Child psychologists and researchers have made their claims through scientific experimentation using carefully selected but a limited number of exemplars. Similarly, the textbooks and worksheets followed for teaching and learning categorization skills are static in nature; that is, they present a limited amount of pre-authored learning content that never changes and that is used repeatedly for every individual. This traditional teacher-centred learning pedagogy named 'the instructional model' limits students' creative learning. These strategies focus on mere

* Corresponding author.
*E-mail addresses:* m.a.abbas@leedsbeckett.ac.uk (M. Abbas), gjhwang.academic@gmail.com (G.-J. Hwang), S.Ajayi@leedsbeckett.ac.uk (S. Ajayi), gmustafa@uaar.edu.pk (G. Mustafa), Muhammad.Bilal@uwe.ac.uk (M. Bilal).

https://doi.org/10.1016/j.caeai.2021.100007
Received 27 October 2020; Received in revised form 2 January 2021; Accepted 2 January 2021

delivery of facts through pre-authored learning content. In addition, authoring such learning content not only requires specialized skills, thinking and dedication, but also takes a large amount of time. The instructional pedagogy violates the dynamisms, hence hindering the cognitive syllabus, and especially object categorization learning.

Modelling real-world knowledge is a challenging task; however, Ontologies—a knowledge management approach—have sufficiently contributed to modelling the entities of the world in a formal representation (mainly taxonomic relationships). The taxonomic representation of the available huge-sized ontological knowledge sources, such as DBpedia (Bizer et al., 2009), WordNet (Fellbaum, 2012), Yago (Suchanek et al., 2008) and ConceptNet (Chou et al., 2017) provide modelling of surface-level categorization; however, they lack the function information between the modelled objects as they mainly focus on modelling named entities (NE), and pay less attention to modelling common-sense knowledge. The present work constructs a smart learning environment (Chen et al., 2020; Hwang et al., 2020) for enhancing the personalized learning of a child. An interactive mobile application is proposed here that models and exploits taxonomic knowledge among real-world objects for the dynamic creation of exemplars (learning content) to enhance the object categorization. It enriches the modelled entities with the function information, and performs querying to create dynamic and diverse categorization exemplars (learning content). The quasi-experimental method was used to evaluate the effectiveness of the proposed application in terms of categorization ability learning.

## 2. Literature review

Humans (both adults and children) naturally organize their knowledge into categories, identifying commonalities and discriminations (Kimura et al., 2018; Namy and Clepper, 2010) among member instances which occur in daily life. Categorization happens even if an infant separates food items based on his/her likes and dislikes (Gelman and Meyer, 2011). Similarly, adults do categorization for efficient sorting of their daily life problems. Researchers have reported two main purposes of categorization for both children and adults alike (Gelman and Meyer, 2011; Horst and Simmering, 2015). First, categorization provides a way to store information in such a way that at a time of need individual member items need not be tracked individually. Secondly, inference is supported over knowledge modelled as categorization. In the past decades, issues related to categorization have been widely discussed by researchers in the field of language learning, qualitative child development, perceptual and knowledge-based categorization, cultural knowledge and human intelligence (Kimura et al., 2018). Several researchers have further pointed out that categorization performed by children could represent their beliefs under different domains, such as natural and manmade things (biology), race and gender discrimination (social science), staple and processed foods (health), poor and rich (economics), and so forth (Giganti and Viggiano, 2015).

Psychologists from the child development domain of research have classified category formation as structural and functional categorization (Kimura et al., 2018; Namy and Clepper, 2010). Structural categorization is related to the visible properties (called perceptual) of an object, such as shape, colour and size. This structural categorization can be considered as a form of generic knowledge acquisition (Butler and Markman, 2014). Generic knowledge is the knowledge about kinds of things. Acquisition of generic knowledge is performed by establishing the explicit properties of a given kind of thing. However, a comprehensive philosophical discussion of how we acquire generic knowledge about kinds of things with a limited number of exemplars is provided. In contrast, the present work studies the effect of multiple exemplars in the acquisition of such knowledge. On the other hand, generic knowledge and structural categorization are of less use while experiencing material culture (Hernik and Csibra, 2009). Material culture represents manmade artefacts, for example, tools and instruments with specific functional information. Learning about objects such as tools and instruments requires functional understanding or the functional categorization ability (Futó et al., 2010). A similar aspect of functional categorization in ecological understanding of the animal food chain by the preschool age group was reported by Michael Allen (2017). A multidimensional scaling (MDS) technique was used to evaluate spontaneous categorization of 34 animal species (Allen, 2015). An experiment with 105 British adolescents (mean age 14.5) revealed that functional information dominates categorization. Researchers have reported that children do on-line categorization for novel objects based on their previous experiences (Bornstein and Mash, 2010). The present work investigates the same phenomenon by enhancing the experience of children through practicing diverse and multiple exemplars in a game-like environment.

Research in child categorization has mainly been in the experimental child psychology, cognition, child development and cognitive science related domains (Hwang et al., 2020). The body of knowledge related to child categorization is huge and thus needs a thorough survey (Chen et al., 2020). In terms of the present work, a brief review shows that very few experiments have been performed using technology (Hwang and Fu, 2020). Multiple trials of contextual repetition with a fixed number of items (6 known, 3 novel, and 3 supporting) have been performed using touchscreen computers (Axelsson and Horst, 2014). Contextual repetition has been performed to evaluate word learning through fast mapping. Several educational games are available that claim to foster children's cognitive learning (Mustafa et al., 2019). However, nearly all of them are static in nature; that is, they only display pre-authored learning content stored in their memory to its users. Available educational games for mobile platforms deal with motor activities, word pronunciations, memory building, colouring objects, basic mathematics, and so forth.

Among these activities, only memory belongs to the cognitive syllabus; however, short-term memory building available in the games is not followed by the memorization of long-term structural and functional information. The associated knowledge of an object has never been focused on by the current applications, since they are not designed for it; rather they provide a fun platform for the children. Modelling the domain knowledge through retrieving the concepts and their associated relationships from huge knowledge sources is a challenging task of the present work. Real-world objects are related to other objects through structural and functional properties; however, these properties are missing in the current knowledge sources. Manual insertion of these properties is infeasible as there are millions of entities present in the current knowledge sources. The present work extracts both concepts and their associated relationships from existing knowledge sources to develop the domain model for generating categorization exemplars.

## 3. The proposed ontology-based mobile learning model

The goal of the proposed work is to investigate children's categorization skills learning through experiencing dynamically created exemplars from modelled knowledge, that is, taxonomic relationships among real-world objects.

### 3.1. Modelling structural categorization

The present work proposes a semi-automatic way for modelling domain ontology (named CagOntology). Concepts of the ontology and relationships among them were extracted systematically from the available knowledge sources such as Dbpedia, ConceptNet, Freebase and WordNet. Single and multiple structural categorization is modelled through the use of hierarchical relationships (subClassOf) among concepts. The relatedness among concepts is modelled through properties among concepts. The proposed ontology construction method uses both top-down and bottom-up knowledge construction approaches for domain modelling. The main hierarchical structure of the proposed ontology is constructed through lexical organization of English words named as WordNet. Synsets (cognitive synonyms) in the WordNet forms a taxonomic network through conceptual-semantic interlinking and lexical relationships. Some of the relations among noun synsets are hypernyms, hyponyms, metonyms, meronyms, homonyms and holonyms.

The algorithm for modelling categorization knowledge has been designed to extract noun senses from WordNet and represent them in an Ontology structure. Not all of the nouns of WordNet are useful for us as several nouns are not understandable by a preschool child. From the curriculum survey, a list of all concepts appearing in books and worksheets was enlisted and called the concept stack (CS) (Fig. 1). The algorithm starts by extracting a concept named as the selected concept (SC) from the concept stack. Then all the senses of the SC were extracted from the WordNet local file. Among all senses retrieved, only noun senses were selected for the further procedure. WordNet contains more than one sense against every noun word, so a list of noun senses was formulated and then a loop operation was performed over it. Each noun sense of a noun word is extracted from WordNet and its hypernym information is screened out. Based on the hypernym information, an assertion with the subClassOf property is added to CagOntology. For example, an assertion added to CagOntology, is Chicken subClassOf Poultry. After the addition of the assertion, the superclass concept is pushed back to the CS if not already present.

The CagOntology constructor algorithm translates the hyponym information from the WordNet to insert sub-concept assertions. For example, the subclasses of the concept Poultry in CagOntology are Chicken, Duck, Goose, Turkey and Squab. Similarly, all these extracted concepts are pushed to the CS so that the hierarchy is completed. Relationships among modelled concepts were extracted from ConceptNet assertions. ConceptNet claims to model generic knowledge such as “Sugar is sweet”, and “Yogurt is made from milk” instead of just representing named entities.

Fig. 2 shows some assertions for the Cow concept in ConceptNet. These assertions are used as a link between concepts. For example, Cow RelatedTo Milk leads us to the milk concept, but there is no intermediate entity present between cow and milk where these concepts meet together. On the other side, a direct relationship cannot be inserted between cow and milk because meanings of the RelatedTo property are missing. RelatedTo does not have a specific meaning or it cannot be concluded because cow is related to milk and also cow is related to farm. In this way, RelatedTo has different meanings for different assertions, that is, a cow produces milk and a cow lives on a farm.

The meanings of the ConceptNet property are then extracted by searching knowledge sources for both concepts of the said assertion. The search now not only includes the names of concepts, but also contains the type of each concept, that is, animal for cow and food for milk. Cyc (Sharma and Goolsbey, 2019) returns a result named Bodily Fluid against the query for cow, milk, animal and food. This result was found because milk is a SubClassOf Bodily Fluid and Bodily Fluid contains a link to Mammal, and Mammal is a subClassOf Animal. CagOntology is then enriched by these relationships. Fig. 3 shows the ontology snapshot with added relationships between Food and Animal.

The ontology is verified for inconsistencies after adding a new concept or relationship to the ontology. This verification is done through the use of a reasoner like Fact++ or Hermit. The reasoner produces several inferred relationships (shown as a dotted line in Fig. 3) such as

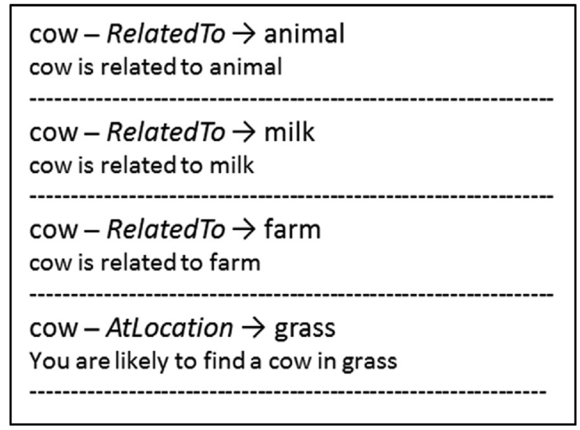


**Fig. 2.** Assertions in ConceptNet for cow.

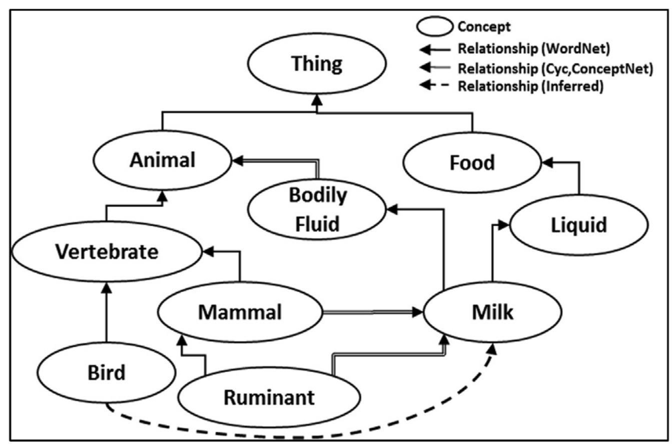


**Fig. 3.** Enriched ontology with a wrongly inferred relationship.

Bird is related to Milk. The reason for this wrongly inferred relationship is because Milk is related to Bodily Fluid and transitively to Animal and Bird.

Every inferred relationship is then cross-checked with the available knowledge sources. The query for bird, milk, animal and food returned null for bird and milk, but several other relations also appeared. An assertion from ConceptNet shown in Fig. 4 provides the Disjoint information, that is, Bird isDisjointWith Mammal and similarly Mammal isDisjointWith Egg and Reptile. The primary reason for using OWL ontologies is to model disjoint and symmetrical information. This disjoint relationship is then added to the ontology.

The reasoner will invoke an error message after the disjoint information is added to the ontology. The reason is that if any two concepts that are disjoint from each other should not be related to the same concept, for example, Bird and Mammal are disjoint but both are related

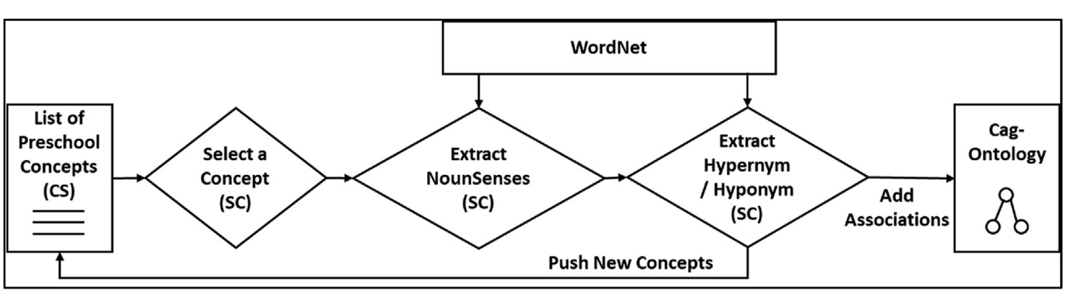


**Fig. 1.** The modelling categorization knowledge algorithm.

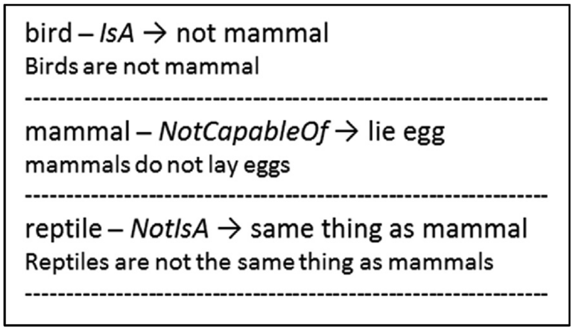


**Fig. 4.** ConceptNet assertions providing disjoint information.

to Milk, this erroneous state is resolved by eliminating the inferred relationship between Bird and Milk as shown in Fig. 5. The order of adding and removing relationships depends on the search results. Any two concepts shall not be annotated with a new common relationship if they were marked as disjoint concepts before.

Properties in WordNet are only structural properties that are used to define the structure of synsets. These properties do not provide relationship/meanings among concepts. Verbs from WordNet are used to define properties among concepts. Symmetric, inverse and transitive property types are carefully inserted through the use of synonyms and hypernym relations of verbs, for example, 'eats' and 'consumes' are symmetric properties. Similarly, individuals are inserted against every concept of populated ontologies. Since the learning content at the preschool level is mainly pictorial representations, images are retrieved from Image-net that represent a concept and the associated concepts in images.

### 3.2. Modelling functional categorization

The present work extends the elementary concepts to support the modelling of complex entities. These entities were named as Abstract Concepts (Functional Information Categorization). In preschool curricula, some examples of the functional categorization concepts are Carnivore, Herbivore, Wild Animal, and Domesticated Animal. A carnivore concept can have birds, reptiles or mammals, but all of them share a common functional characteristic, that is, they feed on meat. The formalism used for the representation of functional categorization is the semantic web rule language (SWRL). SWRL is an extension of ontology web language (OWL) combined with description language (DL) that supports classes, subClassOf relations, equivalent classes, disjoint and symmetrical relations and individual and data properties. This make

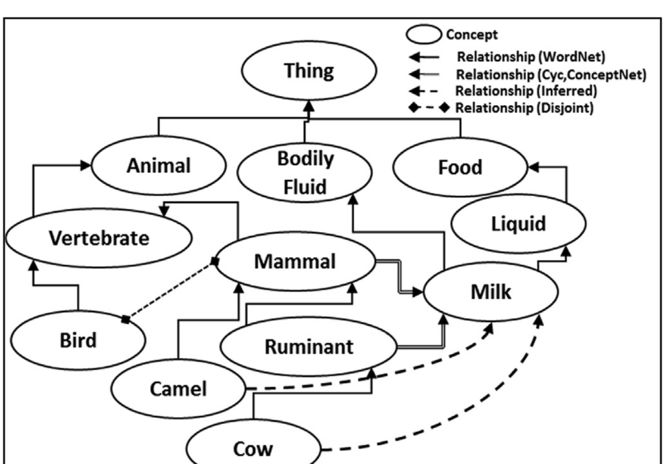


**Fig. 5.** Enriched ontology with correctly inferred relationship.

SWRL a reason for selection in the present work. The present work provides some rules for the representation of abstract concepts that also support an inference or reasoning mechanism.

Carnivore is a functional categorization that is represented by the rule shown in Fig. 6. In Fig. 6 the consequent and antecedent parts of the rule are shown separately. The oval shape represents a class of the ontology, the square shape represents the variable, and the dotted line rectangle represents a property concerned with the variables of the concepts. Similarly, a wild animal is a type of animal that lives in a jungle. Every animal has a property livesIN associated with them, which represents their living habitat. For example, aquatic animals live in water. Fig. 7 shows a pictorial view of the rule for wild animals. Moreover, a combination of different concepts forms a new functional categorization. For example, mammals are the source of milk. There are herbivorous and carnivorous mammals that produce milk, but humans only consume milk from herbivorous mammals. The proposed domain model expresses this distinction, 'Milk' or 'Drinkable Milk', by representing a rule that combines several other abstract concepts as shown in Fig. 8.

### 3.3. Formulation of categorization exemplars

The inference engine is a component of expert systems that makes use of logical rules, concepts and properties to deduce new knowledge, that is, categorization exemplars for the present case. Inference executes rules and performs conflict resolution called reasoning over the knowledge base. The present work uses the forward inference (data-driven reasoning) approach for the creation of the categorization exemplars. The inference engine exploits both modelled rules and relationships among concepts such as inheritance, inverse, transitive, symmetric, differentFrom, allDifferent and disjoint.

The present work utilizes the inheritance relationship for the inference of new concepts or relations. For example, an abstract concept is Animal Groups, that is, Canines live in Packs, Ruminants live in Herds, Insects live in Swarms and Fish live in Schools. The inference using the inheritance relationship is demonstrated as follows. A concept Canine is declared in the ontology as a subclass of Mammal and Carnivore. Canine animals have the property that they hunt in packs. Inference follows the intuitive relationship of inheritance that sub-classes share the general properties of their super-classes (for instance, all canines hunt in a group called a pack; therefore, all sub-classes of canine, e.g. dog, wolf, etc. also have the same relationship with the animal group). Fig. 9 shows the inferred relationship between the subclass of Canine and the Pack concept under the Animal Group, while Tiger is a subclass of feline that does not relate to a pack.

Concepts or relationships are also inferred through transitive assumptions among concepts. For example, if X is part of Y, and Y is part of Z, then X is part of Z. OWL supports the declaration of transitive properties, and the inference mechanism uses such declarations to conclude new concepts. Fig. 10 shows a transitive relation between Cow and Leather Glove. The relation shown in Fig. 10 is as follows: Cow has a part Leather and Leather is a part of Leather Glove. The inferred relationship is the Animal Product, that is, both Leather and Leather Glove are Animal Products. In the same manner, Wool, Milk, Meat, Eggs and Honey are concluded as Animal Products.

To conclude all transitive relationships individually is a cumbersome job. To avoid this, a general rule for inferencing transitive relations is added to the ontology. Fig. 11 shows a representation of the general transitivity present among concepts. Every concept is related with other concepts through property, and every concept has a concept type. For example, in Fig. 10, Cow is a type of Animal class while Leather Glove is an Artefact. Similarly the inference mechanism can conclude that a concept (?Y) is part of two different concept types (?X and ?Z) with the same property (partOf) having a transitive relationship among them. This can be seen in Fig. 12 for Milk Product, that is, Yogurt, Cream, Butter and Cheese.

The already modelled disjoint information within CagOntology

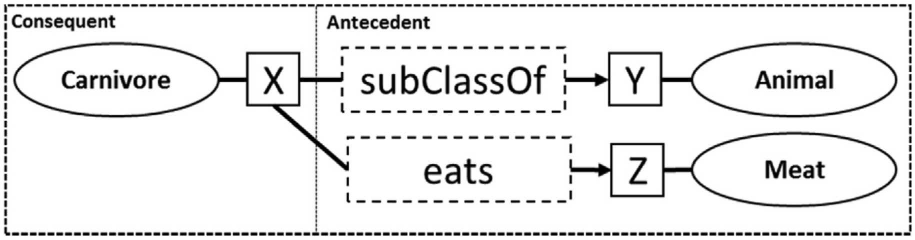


**Fig. 6.** Carnivore concept represented in SWRL

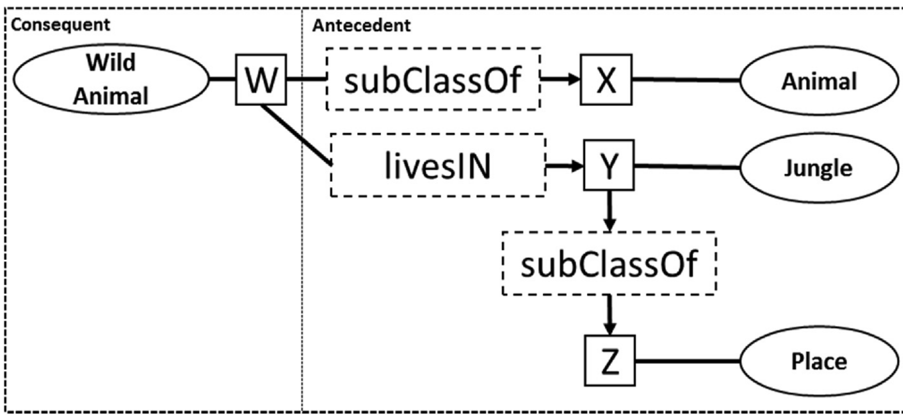


**Fig. 7.** Wild animal concept represented by SWRL

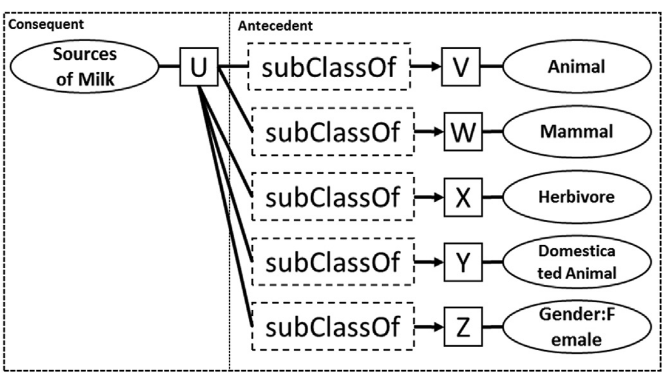


**Fig. 8.** Sources of drinkable milk represented by SWRL

supports the inferencing of some new relationships. Disambiguation is content among the content of object categorization of the preschool cognitive syllabus. Disambiguation requires two or more categorizations that are disjoint from each other. The following disambiguation content is inferred by the inference mechanism using disjoint property information. Fig. 13 shows the inferred disjoint relationship between the Carnivore and Herbivore concepts. Similarly, other disambiguation content like PET and Wild animals are inferred using the disjoint information between Jungle and Farm that are subclasses of the Place concept.

Extending the inference ability, a new concept is inferred by combining two rules with some part common either in antecedent or in consequent. An example is Wild Carnivore (Fig. 14), that can be formulated by the combination of the Wild and Carnivore rules shown in Figs. 6 and 5 respectively.

### 3.4. Prototype implementation

The implementation of the dynamic generation of categorization exemplars through modelled domain knowledge was carried out as a mobile application named CogSkills (cognitive skills). The proposed application was used as an instrument during experimentation. The

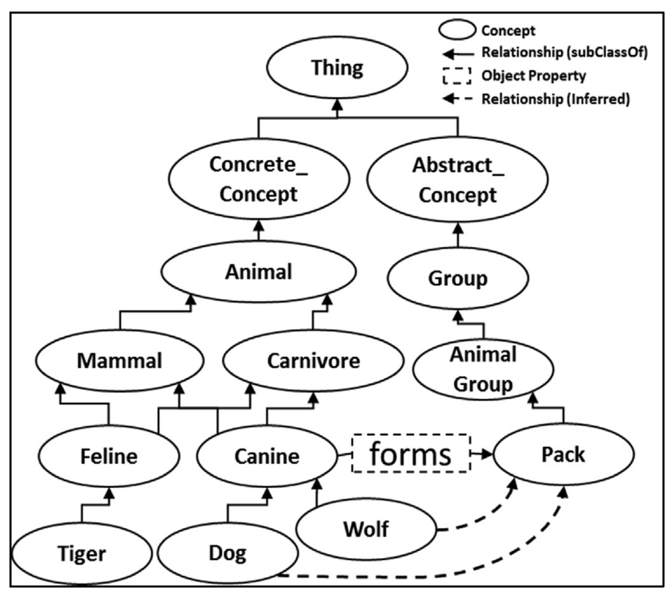


**Fig. 9.** Snapshot of CagOntology – inferred relationships.

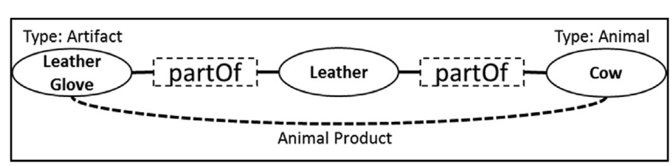


**Fig. 10.** Transitive relationship between concepts.

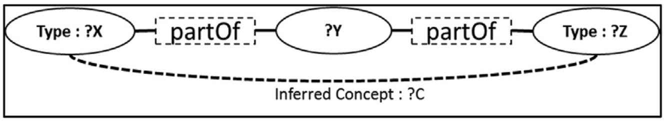


**Fig. 11.** General transitivity relationship.

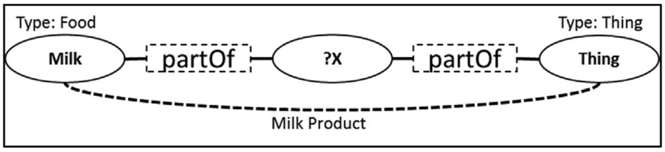


**Fig. 12.** Transitive relationship – milk products.

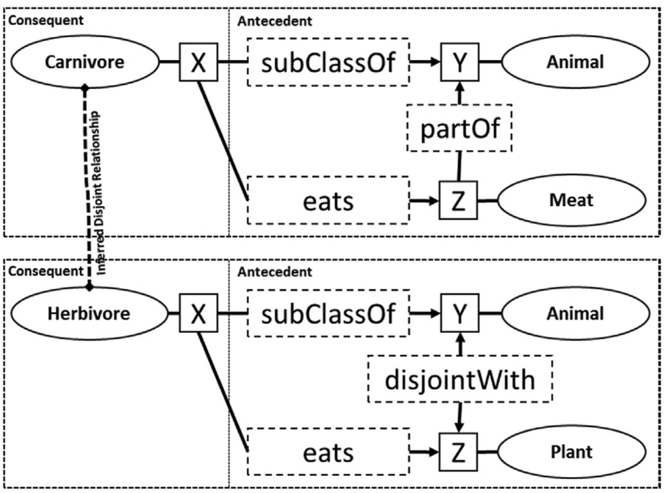


**Fig. 13.** Inferred disjoint relationship.

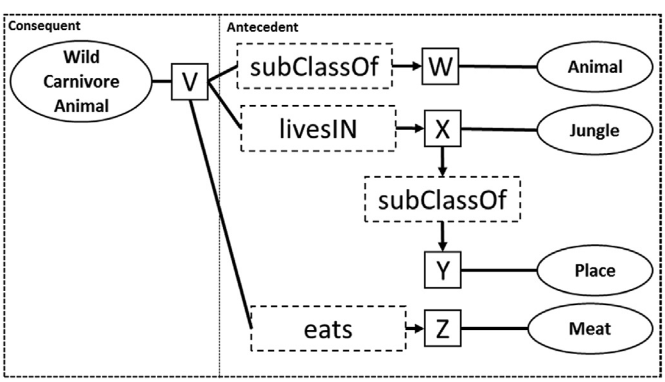


**Fig. 14.** Combination of multiple rules.

proposed application was developed using the Jquery-mobile library that runs on the Android platform. CagOntology is translated to a relational database (RDB) using the SQLite database engine.

In order to administer the categorization skill learning, the proposed application was designed to include both learning and testing modules. Learning of a categorization can be done in the proposed application by demonstrating the essential properties of the target category. Examples of the properties associated with the 'bird' category are beak, wings and two legs. The proposed application uses images to represent both categories and its associated properties. Children can learn through experiencing these properties and categories together in an interactive way (Fig. 15a). The application creates this learning content (as shown in Fig. 15 (b)) through the use concepts and properties of the ontology.

The testing module of the application provides the ability to test both single and multiple categorizations. A single categorization test requires children to identify items of a target categorization from a set of choice alternatives. These test exemplars are generated online using domain ontology. The single categorization test (Fig. 15c) in the proposed application follows the disambiguation cognitive syllabus of the pre-school curriculum. Structural categorization exemplars such as this are mainly created using hierarchical information of a concept in the domain ontology. A child can tap on the required target items to successfully finish the test. For multiple categorizations, CogSkills follows a drag and drop user interface as shown in Fig. 15 (d). Two or more than two categories are tested in a multiple categorization test. However, selection of a different categorization is based on explicit knowledge modelled between categories. Every correct or incorrect answer is locked once it is dropped in any category block. Every exemplar is generated based on the user's profile, explicit knowledge and randomly selecting concepts and their respective individuals. A correct answer is shown with a green box, whereas a red box shows a wrongly tapped or dragged item. CogSkills is a reward-based game where every correct answer assigns a star to the player and every wrong answer deducts a star.

## 4. Experiment and results

To evaluate the effectiveness of the proposed approach, an experiment was conducted to compare the categorization skill learning of the children who experienced the proposed mobile application with the traditional method of teaching using worksheets and textbooks.

### 4.1. Participants

The evaluation was carried out through a quasi-experimental pre- and post-test design method. A sample of 79 children (3–6 years, both male and female) was selected from local preschools through a random sampling selection method. Children were selected from the schools that are following a unified curriculum i.e., Oxford University Press. Intact control and experimental groups were formed by selecting children from different classes in a school to avoid knowledge sharing among them during the experiment period. The control and experimental groups comprised 34 and 45 children, respectively. The children in the control group continued their routine learning practice through class teaching, worksheets and textbooks. Teachers mainly followed the textbooks, but they also regularly provided printed worksheets that were planned in accordance with the ongoing textbook content. The experimental group worked with the proposed mobile application installed on the provided tablets in addition to their routine learning practice. Participants of the experimental group were provided with tablets for approximately 30 min after their school hours. The experiment was conducted in the middle of the academic year for all children. The experiment was continued for 22 days.

Both the pre- and post-test were designed by a senior child psychologist who is a practitioner and a researcher. These tests were very much aligned with the category set experimented with by Kimura et al. (2018). The pre- and post-test were divided into two parts according to the categorization levels, that is, structural and functional categorization (as shown in Table 1). Each structural and functional part of the pre- and post-test contains five exemplars. Each exemplar contains structural items that belong to a single category and possesses a similar perceptual property. Items of the functional categorization can be categorized with respect to a common function. Each exemplar acts as content that contains items of asked categorization and items of choice alternatives mixed together. Choice alternatives are items that physically or functionally resemble the asked category but do not belong to the target category. Moreover, member items of the post-test categories appear as choice alternatives, but post-test categories themselves never appear within the


**Fig. 15.** Prototype Screenshots. a) Learning Module b) Exercise Module c) Test Module Structural Categorization d) Test Module Functional Categorization.

**Table 1**
Pre- and Post-test. Pre- and post-test design.

| Categorization | Pre-test | Cronbach's Alpha Score | Post-test | Cronbach's Alpha Score |
|---|---|---|---|---|
| Structural | Living Things<br>Birds<br>Stationary Items<br>Fruit<br>Occupations | 0.70 | Non-Living Things<br>Fish<br>Sports Equipment<br>Vegetables<br>Vehicles | 0.62 |
| Functional | Herbivores<br>Footwear<br>Wild Animals<br>Source of Milk<br>Floating Objects | 0.60 | Omnivores<br>Headwear<br>Water Vehicles<br>Milk Products<br>Law Occupations | 0.69 |

CogSkills application. This way we ensured the validity of the post-test conductance.

The validation of the pre- and post-tests was carried out using the adult ratings method. A group of 35 postgraduate and undergraduate students in the field of psychology, computer science and education participated in the assessment of the exemplars, items associated with each exemplar and choice alternatives. The assessment was carried out to evaluate the acceptance and suitability of the pre- and post-test content for the children of preschool age. Every evaluator rated all exemplars using a 5-point Likert scale. Evaluators were asked to rate "How suitable is the exemplar in terms of categorization" based on the structural and functional information. The resultant Cronbach's alpha scores of all evaluators are as follows: pre-test structural categorization ($p = 0.70$), pre-test functional categorization ($p = 0.60$), post-test structural categorization ($p = 0.62$) and post-test functional categorization ($p = 0.69$). The acceptable value of alpha $>.60$ was used for the analysis. All objects of tests are represented by a clear picture and labelled with appropriate text. The pictorial representations of the items and categories were validated by two faculty members who are experts in usability, especially in mobile game design.

Each exemplar of the pre- and post-test was scored on a scale of 0–2. Zero represents an incorrect answer, when a child only marks choice alternatives. A partially correct answer is graded with a score of 1 if the answer contains both correct items and choice alternatives. Correct answers were awarded a score of 2. Children were not provided with the type of categorization information within the pre- and post-test. A paper-based test conductance method was used for both the control and experimental groups. All exemplars were presented as a worksheet where the child had to circle the correct items. The other presentational method, that is, match the columns, is not applicable here as the present study only evaluates single structural and functional categorization among multiple objects. However, match the columns is applicable to multiple categorization between a pair of objects that can be a future study of the present research.

### 4.2. Results

Table 2 presents the descriptive results of the pre-test scores. An evaluation can be performed over the pre-test scores to assess that

**Table 2**
Pre-test analysis descriptive statistics.

| | Group | Age Years | N | Mean Structural | Mean Functional | Sum of Mean Score (%) |
|---|---|---|---|---|---|---|
| (X) | Control Group | 3 | 7 | 3.15 | 2.65 | 5.80 (28.98) |
| | | 4 | 9 | 3.61 | 3.26 | 6.87 (34.34) |
| | | 5 | 12 | 4.50 | 4.94 | 9.44 (47.21) |
| | | 6 | 17 | 4.71 | 4.66 | 9.37 (46.85) |
| (Y) | Experimental Group | 3 | 4 | 3.13 | 2.68 | 5.80 (29.20) |
| | | 4 | 7 | 3.65 | 3.16 | 6.81 (34.05) |
| | | 5 | 10 | 4.65 | 5.07 | 9.72 (48.61) |
| | | 6 | 13 | 4.27 | 4.45 | 8.72 (43.60) |

**Table 4**
Post-test analysis descriptive statistics.

| | Group | Age in Years | N | Mean Structural | Mean Functional | Sum of Mean Score (%) |
|---|---|---|---|---|---|---|
| (X) | Control Group | 3 | 7 | 3.93 | 3.47 | 7.40 (37.01) |
| | | 4 | 9 | 4.56 | 4.76 | 9.32 (46.60) |
| | | 5 | 12 | 5.63 | 6.43 | 12.05 (60.27) |
| | | 6 | 17 | 6.06 | 6.72 | 12.78 (63.91) |
| (Y) | Experimental Group | 3 | 4 | 5.13 | 4.64 | 9.77 (48.84) |
| | | 4 | 7 | 5.07 | 6.33 | 11.40 (56.99) |
| | | 5 | 10 | 7.10 | 7.50 | 14.60 (73.00) |
| | | 6 | 13 | 7.77 | 7.64 | 15.41 (77.03) |

participants possess an equal and rudimentary knowledge, that is, categorization ability, before applying the treatment (use of the dynamic categorization exemplars). The overall mean score of the structural categorization is higher than functional categorization for both the control and experimental groups. The higher aged children performed better than the younger ones because younger children are mostly taught memory (counting, alphabet, colour recognition, etc.) and motor (drawing, colouring, etc.) skills rather than categorization and other cognitive syllabuses. However, the pre-test was well designed so that even the younger children achieved scores for both structural and functional categorization. A linear pattern is visible in score achievement by all participants with respect to their ages. At the moment, the present study only considers collective improvement by the participants in terms of categorization ability, but an in-depth study can be conducted to validate the relation between age and categorization ability. Results provided in Table 2 show that the children from both groups achieved similar scores, that is, the control group mean score is 7.87 (1.584 std div) and the experimental group achieved 7.76 (1.541 std div).

A paired sample *t*-test was conducted to analyse the children's categorization skill learning by experiencing the dynamic exemplar creation approach as an independent variable, while the achievement score measured on two different occasions after applying the treatment was a dependent variable. The results of the paired sample *t*-test of the pre-test score achieved by the control and experimental groups is shown in Table 3. From the results, it can be concluded that there was no significant difference in the pre-test scores of the 45 participants in the control group ($M = 7.87$, $SD = 1.584$) and the 34 participants in the experimental group ($M = 7.76$, $SD = 1.541$); $t\,(79) = 0.537, p = 0.868$. These results show that children in both groups possessed an equal level of categorization ability before the treatment.

A descriptive analysis of the post-test score achieved by the control and experimental groups is provided in Table 4. An increment in post-test scores is visible for all children in both groups. Moreover, the experimental group achieved relatively higher scores for functional categorization as compared to the control group. Even younger children in the experimental group showed a substantial increment in functional categorization. A clustered pattern is visible in the post-test scores of the experimental group, that is, younger aged children (3 and 4 years of age) performed closely to each other, while older aged children (5 and 6 years of age) scored the same. The difference in the overall mean value of both groups provides evidence of the categorization skill improvement by the experimental group using the dynamic exemplar application over the control group that followed the traditional teaching methods.

**Table 3**
*t*-test results of the pre-test scores in each group.

| | Group | N | Mean | SD | Mean Difference | t |
|---|---|---|---|---|---|---|
| (X) | Control Group | 45 | 7.87 | 1.584 | 0.043 | 0.537* |
| (Y) | Experimental Group | 34 | 7.76 | 1.541 | | |

*$p > 0.05$.

Analysis of a *t*-test on the post-test scores achieved by both groups is presented in Table 5. As can be seen, a significant effect ($t(79) = -19.870$, $p = 0.000$) was found for the dynamic exemplar learning approach, implying that the post-test scores of the children were significantly different due to the knowledge-based learning models. Thus, the result shows that the children ($M = 12.79$, $SD = 2.301$) who experienced the dynamic creation of categorization exemplars in the game-like approach outperformed those who learned with the conventional instructional learning approach ($M = 10.39$, $SD = 2.154$) in terms of improving their categorization ability.

## 5. Discussion and conclusion

The present work has presented a knowledge-based approach for modelling the structural and functional categorization knowledge of real-world objects. The modelled knowledge is used for dynamic creation of categorization exemplars. It was demonstrated through experimentation using a mobile application that exposure to diverse and multiple categorization exemplars provided enhanced learning of the categorization ability. The children who experienced the dynamically created categorization exemplars from the modelled knowledge achieved increased scores compared to the children who followed the traditional teaching using books and worksheets. The reason for this enhanced categorization learning is that the proposed technique follows the constructive pedagogy that remedies the limitation of traditional instructional pedagogy. Following the student-centred constructive pedagogy, the students were exposed to a learning environment that allowed them to construct new knowledge, and their actions provided an evaluation of their understanding of the concepts. The constructivism is implemented by the inference mechanism over modelled domains and rules to conclude new knowledge or generate new exemplars. Moreover, the present work overcomes the problem of requirements of specialized skills, thinking,

**Table 5**
*t*-test results of the post-test scores in each group.

| | Group | N | Mean | SD | Mean Difference | t |
|---|---|---|---|---|---|---|
| (X) | Control Group | 45 | 10.39 | 2.154 | 2.401 | −19.870* |
| (Y) | Experimental Group | 34 | 12.79 | 2.301 | | |

*$p < 0.05$.

dedication and a large amount of time for the creation of exemplars by using the proposed ontologies-based application.

Another reason for the enhanced categorization learning is that experiencing multiple and diverse categorization exemplars increases the predictability of the target category. Researchers have reported that exposure to multiple tasks of the same nature enhances focus by decreasing visual processing for eliminating alternative choices and in return increases predictability. Like the present work, previously, the benefit of object location repetition in word learning was reported. (Benitez and Smith, 2012). Axelsson and Horst (2014) achieved increased word learning from contextual repetition. This concludes and is supported by a claim made by Benitez and Smith (2012) and Smith et al. (2010) that experiencing exemplars (in our case) increases predictability, which leads to attention and, in return, enhances learning (Deng and Sloutsky, 2016).

It has been reported that computer games can only enhance a cognitive syllabus if they are specifically designed to do so (Martin et al., 2020). The results of the empirical evaluation of the proposed categorization skill learning through a knowledge-based mobile application provides initial evidence that the proposed approach tapped into enhancing categorization skill learning. These findings were tested by comparing the participants' scores. Moreover, this identifies a step towards testing the potential of using knowledge-based mobile applications for categorization skill learning (Chung et al., 2019).

Categorization is a component of the preschool cognitive syllabus that supports lifelong learning. It has been argued that the learning context cannot be easily separated from categorization skill learning. Categorization serves as a stimulus for cognition and development that highly supports educational purposes, such as the importance of categorization in mathematical understanding (Prager et al., 2016), food & nutrition (Nicholson et al., 2018; Rioux et al., 2016), language learning (Axelsson and Horst, 2014; Benitez and Smith, 2012; Smith et al., 2010), goal-directed behaviour (Ackerman and Friedman-Krauss, 2017), working memory & attention (Welsh et al., 2010), child inferencing (Falomir et al., 2020), and so on. In brief, the large number of tasks that are related to categorization skills shows the importance of this central human ability to a wide range of behaviours (Horst and Simmering, 2015).

While conducting the experiment during the present study, it was observed that the pre-school teachers faced difficulties authoring the categorization content. Authoring categorization content, especially for the assessment of functional categorization, requires dedication and time. Placing a member object under multiple categorizations requires concentration and deep thinking. Using text processing software adds more complexity to the authoring process. Parents at home willing to exercise their children's categorization skill have only one option: downloading available worksheets from the Internet. Searching for appropriate and substantial numbers of worksheets over the Internet is quite a difficult task. Content available on the Internet is mainly non-editable. Teachers make copies of the previous content and use the same copy repeatedly for every student. The proposed knowledge-based approach highly supports teaching activities both at school and home by presenting a method for convenient authoring of categorization content.

Several aspects of the present work need further investigation, such as evaluation of mistakes performed by the children during application use, cognitive load, the effect of a single exemplar repetition, usability, and the relationship between functional and contextual knowledge. It was observed that the computational limitations of the mobile platform affected the children's enjoyment as creation of every new exemplar takes a noticeable amount of time. However, web platforms or mobile applications using web services will be more suited to the proposed approach.

## Declaration of competing interest

There is no potential conflict of interest in this study. The data can be obtained by sending request e-mails to the corresponding author.

## References


Ackerman, D. J., & Friedman-Krauss, A. H. (2017). Preschoolers' executive function: importance, contributors, research needs and assessment options. *ETS Research Report Series, 2017*(1), 1–24. https://doi.org/10.1002/ets2.12148

Allen, M. (2015). Preschool children's taxonomic knowledge of animal species. *J. Res. Sci. Teach., 52*(1), 107–134. https://doi.org/10.1002/tea.21191

Allen, M. (2017). Early understandings of simple food chains: a learning progression for the preschool years. *Int. J. Sci. Educ., 39*(11), 1485–1510. https://doi.org/10.1080/09500693.2017.1336809

Axelsson, E. L., & Horst, J. S. (2014). Contextual repetition facilitates word learning via fast mapping. *Acta Psychol., 152*, 95–99. https://doi.org/10.1016/j.actpsy.2014.08.002

Benitez, V. L., & Smith, L. B. (2012). Predictable locations aid early object name learning. *Cognition, 125*(3), 339–352. https://doi.org/10.1016/j.cognition.2012.08.006

Bizer, C., Lehmann, J., Kobilarov, G., Auer, S., Becker, C., Cyganiak, R., & Hellmann, S. (2009). DBpedia - a crystallization point for the Web of Data. *Web Semant. Sci. Serv. Agents World Wide Web, 7*(3), 154–165. https://doi.org/10.1016/j.websem.2009.07.002

Bornstein, M. H., & Mash, C. (2010). Experience-based and on-line categorization of objects in early infancy. *Child Dev., 81*(3), 884–897. https://doi.org/10.1111/j.1467-8624.2010.01440.x

Butler, L. P., & Markman, E. M. (2014). Preschoolers use pedagogical cues to guide radical reorganization of category knowledge. *Cognition, 130*(1), 116–127. https://doi.org/10.1016/j.cognition.2013.10.002

Chen, X., Xie, H., Zou, D., & Hwang, G.-J. (2020). Application and theory gaps during the rise of artificial intelligence in education. *Comput. Educ.: Artif. Intell., 1*, 100002. https://doi.org/10.1016/j.caeai.2020.100002

Chou, P.-H., Tsai, R. T.-H., & Hsu, J. Y. (2017). Context-aware sentiment propagation using LDA topic modeling on Chinese ConceptNet. *Soft Computing, 21*(11), 2911–2921.

Chung, C.-J., Hwang, G.-J., & Lai, C.-L. (2019). A review of experimental mobile learning research in 2010–2016 based on the activity theory framework. *Comput. Educ., 129*, 1–13. https://doi.org/10.1016/j.compedu.2018.10.010

Deng, W. Sophia, & Sloutsky, V. M. (2016). Selective attention, diffused attention, and the development of categorization. *Cognit. Psychol., 91*, 24–62. https://doi.org/10.1016/j.cogpsych.2016.09.002

Falomir, Z., Gibert, K., & Plaza, E. (2020). Special issue on pattern recognition and cognitive assistants. *Pattern Recogn. Lett., 133*, 295–297. https://doi.org/10.1016/j.patrec.2020.03.017

Fellbaum, C. (2012). *WordNet. The Encyclopedia of Applied Linguistics*. MIT Press. https://doi.org/10.1002/9781405198431.wbeal1285

Futó, J., Téglás, E., Csibra, G., & Gergelya, G. (2010). Communicative Function Demonstration induces kind-based artifact representation in preverbal infants. *Cognition, 117*(1), 1–8. https://doi.org/10.1016/j.cognition.2010.06.003

Gelman, S. A., & Meyer, M. (2011). Child categorization. *Wiley Interdisciplinary Reviews: Cognit. Sci., 2*(1), 95–105. https://doi.org/10.1002/wcs.96

Giganti, F., & Viggiano, M. P. (2015). How semantic category modulates preschool children's visual memory. *Child Neuropsychol., 21*(6), 849–855. https://doi.org/10.1080/09297049.2014.945406

Hernik, M., & Csibra, G. (2009). Functional understanding facilitates learning about tools in human children. *Curr. Opin. Neurobiol., 19*(1), 34–38. https://doi.org/10.1016/j.conb.2009.05.003

Horst, J. S., & Simmering, V. R. (2015). Category learning in a dynamic world. *Front. Psychol., 6*, 46. https://doi.org/10.3389/fpsyg.2015.00046

Hwang, G.-J., & Fu, Q.-K. (2020). Advancement and research trends of smart learning environments in the mobile era. *Int. J. Mobile Learn. Organisat., 14*(1), 114–129.

Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. *Comput. Educ.: Artif. Intell., 1*, 100001. https://doi.org/10.1016/j.caeai.2020.100001

Kimura, K., Hunley, S. B., & Namy, L. L. (2018). Children's use of comparison and function in novel object categorization. *J. Exp. Child Psychol., 170*, 161–176. https://doi.org/10.1016/j.jecp.2017.12.016

Martin, F., Sun, T., & Westine, C. D. (2020). A systematic review of research on online teaching and learning from 2009 to 2018. *Comput. Educ., 159*, 104009. https://doi.org/10.1016/j.compedu.2020.104009

Moem. (2001). National pre-school curriculum ministry of education Malaysia. http://www.moe.gov.my/bpk/sp_hsp/pra/sp_prasekolah.pdf.

Moes. (2012). *Nurturing Early Learners - A Curriculum Framework for Kindergartens in Singapore*. http://moe.gov.sg/education/preschool/.

Mustafa, G., Abbas, M. A., Hafeez, Y., Khan, S., & Hwang, G.-J. (2019). Effectiveness of ontology-based learning content generation for preschool cognitive skills learning. *Interact. Learn. Environ., 27*(4), 443–457.

Namy, L. L., & Clepper, L. E. (2010). The differing roles of comparison and contrast in children's categorization. *J. Exp. Child Psychol., 107*(3), 291–305. https://doi.org/10.1016/j.jecp.2010.05.013

Nicholson, J. S., Barton, J. M., & Simons, A. L. (2018). Ability to categorize food predicts hypothetical food choices in head start preschoolers. *J. Nutr. Educ. Behav., 50*(3), 238–246. https://doi.org/10.1016/j.jneb.2017.09.026. e1.

Prager, E. O., Sera, M. D., & Carlson, S. M. (2016). Executive function and magnitude skills in preschool children. *J. Exp. Child Psychol., 147*, 126–139. https://doi.org/10.1016/j.jecp.2016.01.002

Quinn, P. C., Lee, K., & Pascalis, O. (2020). In J. B. Benson (Ed.), *Chapter Two - beyond Perceptual Development: Infant Responding to Social Categories* (vol. 58, pp. 35–61). JAI. https://doi.org/10.1016/bs.acdb.2020.01.002.

Rioux, C., Picard, D., & Lafraire, J. (2016). Food rejection and the development of food categorization in young children. *Cognit. Dev., 40*, 163–177. https://doi.org/10.1016/j.cogdev.2016.09.003

Sharma, A., & Goolsbey, K. M. (2019). Simulation-based approach to efficient commonsense reasoning in very large knowledge bases. *Proceedings of the AAAI Conference on Artificial Intelligence, 33*, 1360–1367. https://doi.org/10.1609/aaai.v33i01.33011360, 01.

Smith, L. B., Colunga, E., & Yoshida, H. (2010). Knowledge as process: contextually cued attention and early word learning. *Cognit. Sci., 34*(7), 1287–1314. https://doi.org/10.1111/j.1551-6709.2010.01130.x

Suchanek, F. M., Kasneci, G., & Weikum, G. (2008). YAGO: a large ontology from wikipedia and WordNet. *Web Semant. Sci. Serv. Agents World Wide Web, 6*(3), 203–217. https://doi.org/10.1016/j.websem.2008.06.001

Welsh, J. A., Nix, R. L., Blair, C., Bierman, K. L., & Nelson, K. E. (2010). The development of cognitive skills and gains in academic school readiness for children from low-income families. *J. Educ. Psychol., 102*(1), 43.

Zou, D., Wang, M., Xie, H., Cheng, G., Wang, F. L., & Lee, L.-K. (2020). A comparative study on linguistic theories for modeling EFL learners: facilitating personalized vocabulary learning via task recommendations. *Interact. Learn. Environ.*, 1–13. https://doi.org/10.1080/10494820.2020.1789178, 0(0.